

ACS Statistical Machine Translation

Lecture 8: Hierarchical Phrase-based Translation



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Statistical Machine Translation (SMT) ¹

Translate s into t :

“Any target word sequence t is a possible translation of the input source sentence s ”

Translating \equiv **Finding** the best hypothesis

$$\hat{t} = \operatorname{argmax}_{t \in \mathcal{T}} P(t|s) = \operatorname{argmax}_{t \in \mathcal{T}} \underbrace{P(s|t)}_{\substack{\text{Translation} \\ \text{Model}}} \underbrace{P(t)}_{\substack{\text{Language} \\ \text{Model}}}$$

- ▶ Translation Model: **from phrases to hierarchical phrases**
- ▶ Language Model is a standard N-gram model

HARD: $|\mathcal{T}|$ can be very large (at most V^I)

¹Brown, P. et al. 1990. A Statistical Approach to Machine Translation. Computational Linguistics, Vol.16, Num.2.

Motivation

Example:

澳洲 是 与 北韩 有 邦交 的 少数 国家 之一 。

Aozhou shi yu Beihan you bangjiao de shaoshu guojia zhiyi .

Australia is with North Korea have dipl. rels. that few countries one of .

Australia is one of the few countries that have diplomatic relations with North Korea.

Limitation of Phrase-based SMT:

[Aozhou] [shi]₁ [yu Beihan]₂ [you] [bangjiao] [de shaoshu guojia zhiyi] [.]

[Australia] [has] [dipl. rels.] [with North Korea]₂ [is]₁ [one of the few countries] [.]

Distorsion limits (maximum jump distance, ...) required to avoid computational explosion prohibit the correct reordering

Motivation (2)

With **Hierarchical Phrases**:

$\langle \text{yu } X_{[1]} \text{ you } X_{[2]}, \text{ have } X_{[2]} \text{ with } X_{[1]} \rangle$
 $\langle X_{[1]} \text{ de } X_{[2]}, \text{ the } X_{[2]} \text{ that } X_{[1]} \rangle$
 $\langle X_{[1]} \text{ zhiyi, one of } X_{[1]} \rangle$

Translation would be possible:

[Aozhou] [shi] [[[yu [Beihan]₁ you [bangjiao]₂] de [shaoshu guojia]₃] zhiyi]

[Australia] [is] [one of [the [few countries]₃ that [have [dipl. rels.]₂ with [N. Korea]₁]]]

Hierarchical Phrase-based Translation

- $R_1: S \rightarrow \langle X, X \rangle$
- $R_2: S \rightarrow \langle S X, S X \rangle$
- $R_3: X \rightarrow \langle s_1, \text{said} \rangle$
- $R_4: X \rightarrow \langle s_1 s_2, \text{the president said} \rangle$
- $R_5: X \rightarrow \langle s_1 s_2 s_3, \text{Syrian president says} \rangle$
- $R_6: X \rightarrow \langle s_2, \text{president} \rangle$
- $R_7: X \rightarrow \langle s_3, \text{the Syrian} \rangle$
- $R_8: X \rightarrow \langle s_4, \text{yesterday} \rangle$
- $R_9: X \rightarrow \langle s_5, \text{that} \rangle$
- $R_{10}: X \rightarrow \langle s_6, \text{would return} \rangle$
- $R_{11}: X \rightarrow \langle s_6, \text{he would return} \rangle$

s_1 s_2 s_3 s_4 s_5 s_6
 wqAl Alr}ys Alswry Ams Anh syEwd
 (وقال الرئيس السوري امس انه سيعود)

Hierarchical Phrase-based Translation

said



$R_1: S \rightarrow \langle X, X \rangle$

$R_2: S \rightarrow \langle S X, S X \rangle$

$R_3: X \rightarrow \langle s_1, \text{said} \rangle$

$R_4: X \rightarrow \langle s_1 s_2, \text{the president said} \rangle$

$R_5: X \rightarrow \langle s_1 s_2 s_3, \text{Syrian president says} \rangle$

$R_6: X \rightarrow \langle s_2, \text{president} \rangle$

$R_7: X \rightarrow \langle s_3, \text{the Syrian} \rangle$

$R_8: X \rightarrow \langle s_4, \text{yesterday} \rangle$

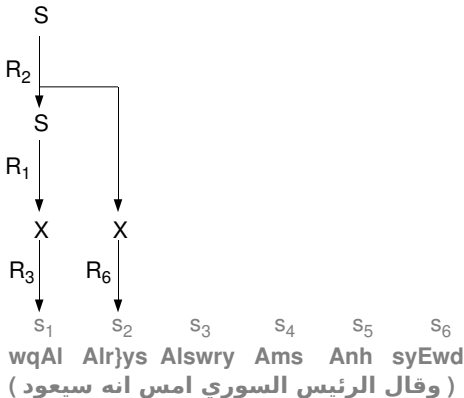
$R_9: X \rightarrow \langle s_5, \text{that} \rangle$

$R_{10}: X \rightarrow \langle s_6, \text{would return} \rangle$

$R_{11}: X \rightarrow \langle s_6, \text{he would return} \rangle$

Hierarchical Phrase-based Translation

said president



$R_1: S \rightarrow \langle X, X \rangle$

$R_2: S \rightarrow \langle S X, S X \rangle$

$R_3: X \rightarrow \langle s_1, \text{said} \rangle$

$R_4: X \rightarrow \langle s_1 s_2, \text{the president said} \rangle$

$R_5: X \rightarrow \langle s_1 s_2 s_3, \text{Syrian president says} \rangle$

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$R_8: X \rightarrow \langle s_4, \text{yesterday} \rangle$

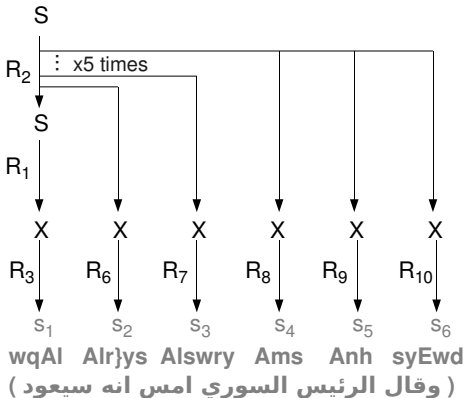
$R_9: X \rightarrow \langle s_5, \text{that} \rangle$

$R_{10}: X \rightarrow \langle s_6, \text{would return} \rangle$

$R_{11}: X \rightarrow \langle s_6, \text{he would return} \rangle$

Hierarchical Phrase-based Translation

said president the Syrian yesterday that would return



R₁: S → ⟨X, X⟩

R₂: S → ⟨S X, S X⟩

R₃: X → ⟨s₁, said⟩

R₄: X → ⟨s₁ s₂, the president said⟩

R₅: X → ⟨s₁ s₂ s₃, Syrian president says⟩

R₆: X → ⟨s₂, president⟩

R₇: X → ⟨s₃, the Syrian⟩

R₈: X → ⟨s₄, yesterday⟩

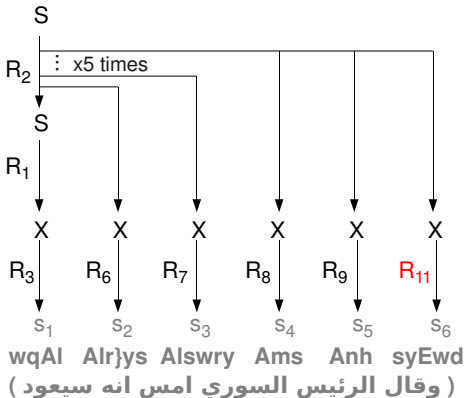
R₉: X → ⟨s₅, that⟩

R₁₀: X → ⟨s₆, would return⟩

R₁₁: X → ⟨s₆, he would return⟩

Hierarchical Phrase-based Translation

said president the Syrian yesterday that **he would return**



R₁: S → ⟨X, X⟩

R₂: S → ⟨S X, S X⟩

R₃: X → ⟨s₁, said⟩

R₄: X → ⟨s₁ s₂, the president said⟩

R₅: X → ⟨s₁ s₂ s₃, Syrian president says⟩

R₆: X → ⟨s₂, president⟩

R₇: X → ⟨s₃, the Syrian⟩

R₈: X → ⟨s₄, yesterday⟩

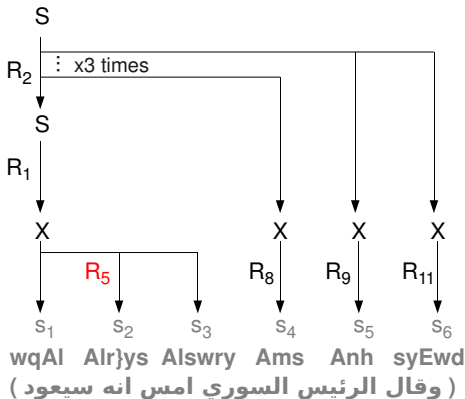
R₉: X → ⟨s₅, that⟩

R₁₀: X → ⟨s₆, would return⟩

R₁₁: X → ⟨s₆, he would return⟩

Hierarchical Phrase-based Translation

Syrian president says yesterday that he would return



R₁: S → ⟨X, X⟩

R₂: S → ⟨S X, S X⟩

R₃: X → ⟨s₁, said⟩

R₄: X → ⟨s₁ s₂, the president said⟩

R₅: **X** → **⟨s₁ s₂ s₃, Syrian president says⟩**

R₆: X → ⟨s₂, president⟩

R₇: X → ⟨s₃, the Syrian⟩

R₈: X → ⟨s₄, yesterday⟩

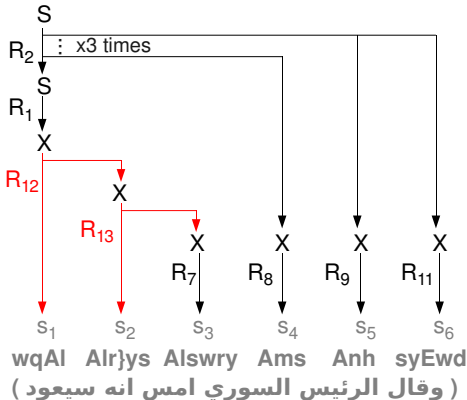
R₉: X → ⟨s₅, that⟩

R₁₀: X → ⟨s₆, would return⟩

R₁₁: X → ⟨s₆, he would return⟩

Hierarchical Phrase-based Translation (2)

the Syrian president said yesterday that he would return



$R_1: S \rightarrow \langle X, X \rangle$

$R_2: S \rightarrow \langle S X, S X \rangle$

$R_3: X \rightarrow \langle s_1, \text{said} \rangle$

...

$R_6: X \rightarrow \langle s_2, \text{president} \rangle$

$R_7: X \rightarrow \langle s_3, \text{the Syrian} \rangle$

$R_8: X \rightarrow \langle s_4, \text{yesterday} \rangle$

$R_9: X \rightarrow \langle s_5, \text{that} \rangle$

$R_{10}: X \rightarrow \langle s_6, \text{would return} \rangle$

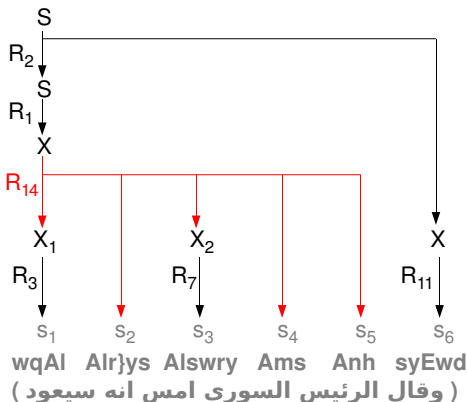
$R_{11}: X \rightarrow \langle s_6, \text{he would return} \rangle$

$R_{12}: X \rightarrow \langle s_1 X, X \text{ said} \rangle$

$R_{13}: X \rightarrow \langle s_2 X, X \text{ president} \rangle$

Hierarchical Phrase-based Translation (2)

yesterday the Syrian president said that he would return



- Each rule has a probability assigned by the Translation Model

Keeping Track of All Derivations. CYK Grid

	S	X					
			X				
				X			
					X		
						X	
							X
	s_1	s_2	s_3	s_4	s_5	s_6	
	wqAl	Alr}ys	Alswry	Ams	Anh	syEwd	

$R_1: S \rightarrow \langle X, X \rangle$

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Keeping Track of All Derivations. CYK Grid

	S	X					
			X				
				X			
					X		
						X	
							X
	R ₃	R ₆	R ₇	R ₈	R ₉	R ₁₀ R ₁₁	
	s ₁	s ₂	s ₃	s ₄	s ₅	s ₆	
	wqAl	Alr}ys	Alswry	Ams	Anh	syEwd	

- R₁: S → (X, X)
- R₂: S → (S X, S X)
- R₃: X → (s₁, said)
- R₄: X → (s₁ s₂, the president said)
- R₅: X → (s₁ s₂ s₃, Syrian president says)
- R₆: X → (s₂, president)
- R₇: X → (s₃, the Syrian)
- R₈: X → (s₄, yesterday)
- R₉: X → (s₅, that)
- R₁₀: X → (s₆, would return)
- R₁₁: X → (s₆, he would return)

Keeping Track of All Derivations. CYK Grid

	S	X					
			X				
				X			
					X		
	R ₅					X	
	R ₄						X
	R ₃	R ₆	R ₇	R ₈	R ₉	R ₁₀ R ₁₁	
	s ₁	s ₂	s ₃	s ₄	s ₅	s ₆	
	wqAl	Alr}ys	Alswry	Ams	Anh	syEwd	

R₁: S → (X, X)

R₂: S → (S X, S X)

R₃: X → (s₁, said)

R₄: X → (s₁ s₂, the president said)

R₅: X → (s₁ s₂ s₃, Syrian president says)

R₆: X → (s₂, president)

R₇: X → (s₃, the Syrian)

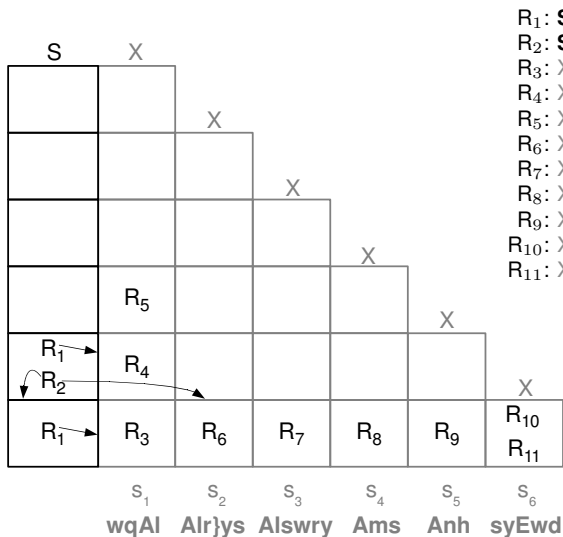
R₈: X → (s₄, yesterday)

R₉: X → (s₅, that)

R₁₀: X → (s₆, would return)

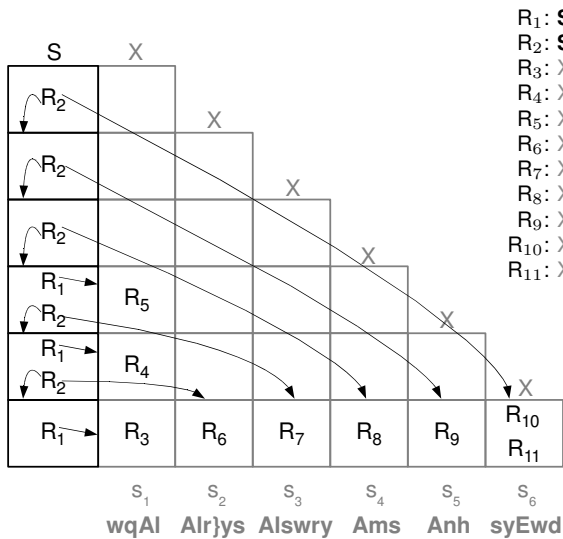
R₁₁: X → (s₆, he would return)

Keeping Track of All Derivations. CYK Grid



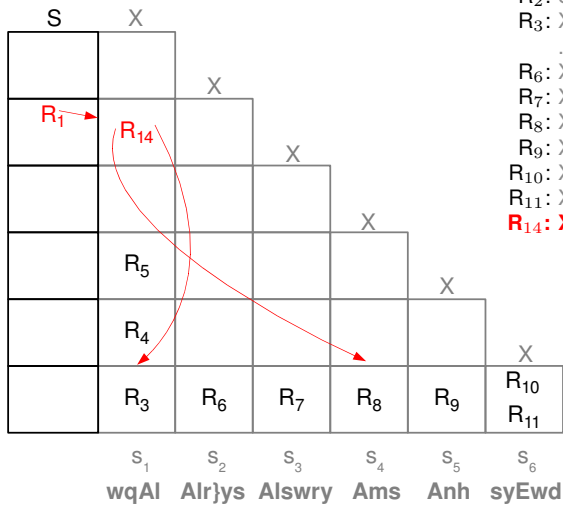
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- R₉: X → (s₅, that)
- R₁₀: X → (s₆, would return)
- R₁₁: X → (s₆, he would return)

Keeping Track of All Derivations. CYK Grid



- $R_1: S \rightarrow (X, X)$
- $R_2: S \rightarrow (SX, SX)$
- $R_3: X \rightarrow (s_1, \text{said})$
- $R_4: X \rightarrow (s_1 s_2, \text{the president said})$
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- $R_7: X \rightarrow (s_3, \text{the Syrian})$
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- $R_9: X \rightarrow (s_5, \text{that})$
- $R_{10}: X \rightarrow (s_6, \text{would return})$
- $R_{11}: X \rightarrow (s_6, \text{he would return})$

Keeping Track of All Derivations. CYK Grid (2)


 $R_1: S \rightarrow (X, X)$
 $R_2: S \rightarrow (S X, S X)$
 $R_3: X \rightarrow (s_1, \text{said})$

...

 $R_6: X \rightarrow (s_2, \text{president})$
 $R_7: X \rightarrow (s_3, \text{the Syrian})$
 $R_8: X \rightarrow (s_4, \text{yesterday})$
 $R_9: X \rightarrow (s_5, \text{that})$
 $R_{10}: X \rightarrow (s_6, \text{would return})$
 $R_{11}: X \rightarrow (s_6, \text{he would return})$
 $R_{14}: X \rightarrow (X_1 s_2 X_2 s_4 s_5, \text{y'day } X_2 \text{ president } X_1 \text{ that})$

Cube Pruning Algorithm ²

- ▶ The number of derivations can be vast
- ▶ Each derivation will produce a translation candidate
- ▶ Each candidate has a score
- ▶ Find best candidate

$$\operatorname{argmax}_{t \in \mathcal{T}} P(s|t) P(t)$$

S	X		
x8420	x20		
x420	x20		
x20	x20	x20	x20
	s_1	s_2	s_3

²Chiang, D. 2005. A Hierarchical Phrase-Based Model for Statistical Machine Translation. *Proc. ACL*.

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x8420	x20		
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x20	x20	x20	x20
	s_1	s_2	s_3

▶ Cube-Pruning Algorithm

- ▶ One-by-one processing of all derivations is not feasible
- ▶ Lists of k -best hypotheses are kept in each cell ($k=10^4$)
- ▶ Local decisions based on Translation and Language Model
- ✓ Translation Model fits well in this grid representation
- ✗ Language Model does not: $P(t) = \prod_{n=1}^T p(t_n|t_{n-1})$

would return $\leftarrow p(\text{return}|\text{would}) \times p(\text{would}|?)$

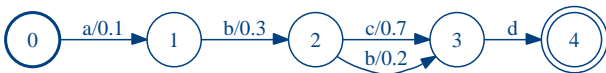
he would return $\leftarrow p(\text{return}|\text{would}) \times p(\text{would}|\text{he}) \times p(\text{he}|?)$

- ▶ Local decisions should be avoided!

²Chiang, D. 2005. A Hierarchical Phrase-Based Model for Statistical Machine Translation. *Proc. ACL*.

Reviewing Weighted Finite-State Acceptors (WFSA)

- ▶ WFSA are devices that compactly model a formal language
- ▶ A **Weighted Acceptor** of strings 'a b c d' and 'a b b d' :



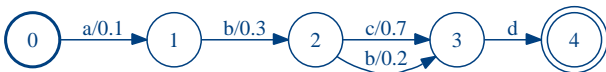
is defined by a set of states Q and a set of arcs : $q \xrightarrow{x/w} q'$

- ▶ Weighted Acceptors can assign costs to strings:
 - strings are associated with paths, which are sequences of arcs
 - weights are accumulated over paths by means of a **product operation** \otimes

$$w(p) = w(e_1) \otimes \cdots \otimes w(e_n)$$

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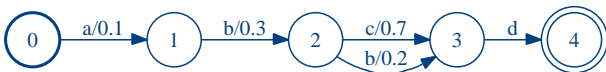
$$w(p) = w(e_1) \otimes \cdots \otimes w(e_n)$$

Probability Semiring: $w('a b c d') = 0.1 \times 0.3 \times 0.7 \times 1.0 = 0.021$ ← BEST

$w('a b b d') = 0.1 \times 0.3 \times 0.2 \times 1.0 = 0.006$

Reviewing Weighted Finite-State Acceptors (WFSAs)

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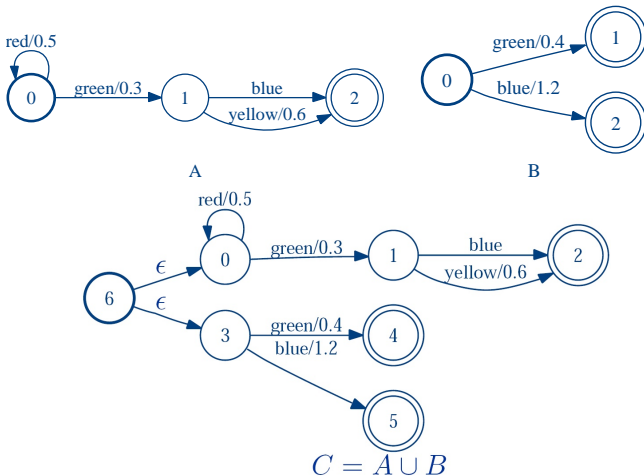
$$w(p) = w(e_1) \otimes \cdots \otimes w(e_n)$$

Tropical Semiring: $w(\text{'a b c d'}) = 0.1 + 0.3 + 0.7 + 0.0 = 1.1$
 $w(\text{'a b b d'}) = 0.1 + 0.3 + 0.2 + 0.0 = 0.6 \leftarrow \text{BEST}$

WFSA Operations - Union

A string x is accepted by $A = A \cup B$ if x is accepted by A or by B

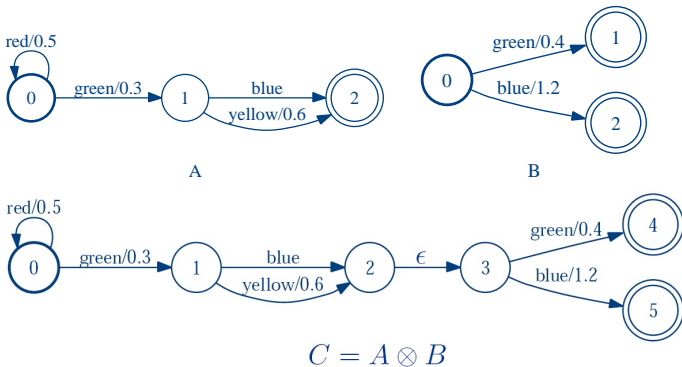
$$\llbracket C \rrbracket(x) = \llbracket A \rrbracket(x) \oplus \llbracket B \rrbracket(x)$$



WFSA Operations - Concatenation (or Product)

A string x is accepted by $C = A \otimes B$ if x can be split into $x = x_1 x_2$ such that x_1 is accepted by A and x_2 is accepted by B

$$[[C]](x) = \bigoplus_{x_1, x_2: x=x_1 x_2} [[A]](x_1) \otimes [[B]](x_2)$$



WFSA Operations for Compactness

WFSAFs can be **made compact** with operations that:

- ▷ reduce their size in number of states/arcs
- ▷ accept the same distinct strings
- ▷ *the cost of each string is respected* according to the semiring



- ▷ WFSAFs can represent compactly more than 10^{60} paths
- ▷ Processing a WFSA is much faster than processing all of the paths individually

HiFST. Hierarchical Translation with WFSTs³

- ▶ Keep all possible derivations in each cell
Efficiently explore largest \mathcal{T} in

$$\operatorname{argmax}_{t \in \mathcal{T}} P(s|t) P(t)$$

S	X		
x8420	x20		
x420	x20		
x20	x20	x20	x20
	s_1	s_2	s_3

- ▶ **Build a WFSA in each cell**
 - ▶ They compactly store millions of paths with Translation Model costs
 - ▶ We can operate with them easily and faster
 - ▶ Applying a Language Model to a WFSA is a well-established task

In each cell, do:

For each rule in the cell:

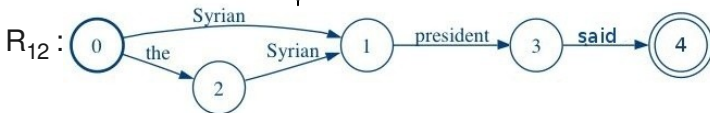
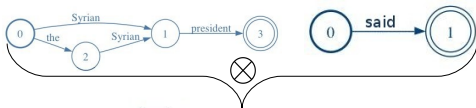
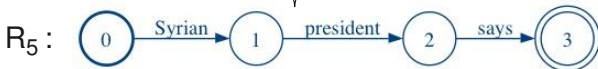
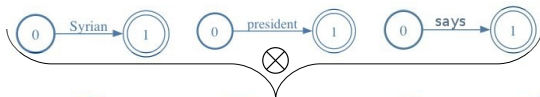
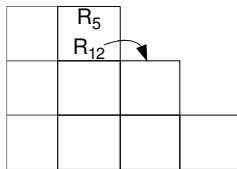
Build Rule WFSA by **Concatenating** target elements (\otimes)

Build Cell WFSA by **Unioning** Rule WSFAs (\oplus)

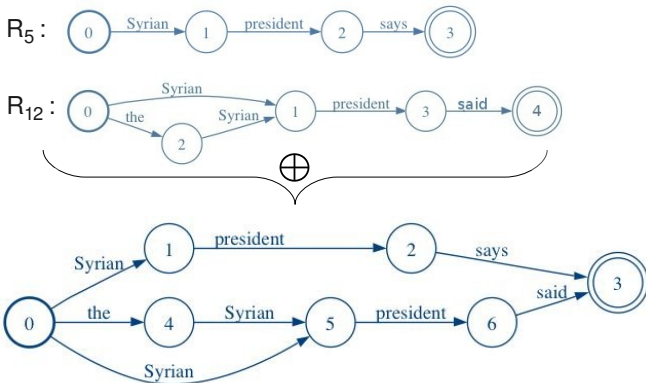
³Iglesias, G. et al. 2009. Hierarchical Phrase-Based Translation with Weighted Finite State Transducers. Proc. of NAACL-HLT.

Building Rule WFSTs by Concatenation

$R_5: \mathbf{X} \rightarrow \langle \mathbf{s}_1 \mathbf{s}_2 \mathbf{s}_3, \mathbf{Syrian\ president\ says} \rangle$
 $R_{12}: \mathbf{X} \rightarrow \langle \mathbf{s}_1 \mathbf{X}, \mathbf{X\ said} \rangle$

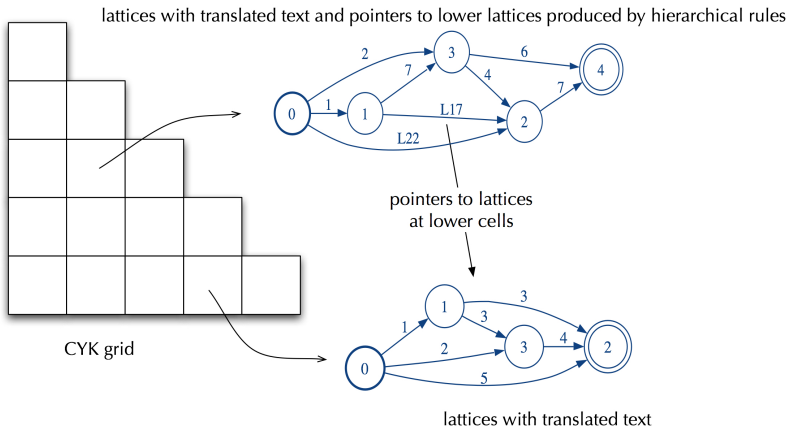


Building Cell WFSA by Union



- ▶ Can be made compact
- ▶ Target language model can be applied
- ▶ Search can be carried out efficiently

Delayed Translation



- ✓ Easy implementation with FST Replace operation
- ✓ Usual FST operations can be applied to skeleton → lattice size reduction

Pruning

Final translation lattice $L(S, 1, J)$ typically requires pruning

- ▶ Compose with target Language Model
- ▶ Perform likelihood-based pruning

Pruning in Search:

- ▶ If number of states, non-terminal category and source span meet certain conditions, then:
 - ▷ Expand Pointers in translation Lattice and Compose with Language Model
 - ▷ Perform likelihood-based pruning of the lattice
 - ▷ Remove Language Model
- ▶ Only required for certain language pairs, i.e. Chinese→English
- ▶ The hierarchical grammar can be defined to avoid this (next lecture)

Translation Experiments into English

▶ Large collections of parallel text are available

- Arabic-to-English: $\sim 6\text{M}$ sentences, $\sim 150\text{M}$ words
- Chinese-to-English: $\sim 10\text{M}$ sentences, $\sim 250\text{M}$ words
- Spanish-to-English: $\sim 1.3\text{M}$ sentences, $\sim 37\text{M}$ words

▶ Hierarchical phrases are extracted from alignments

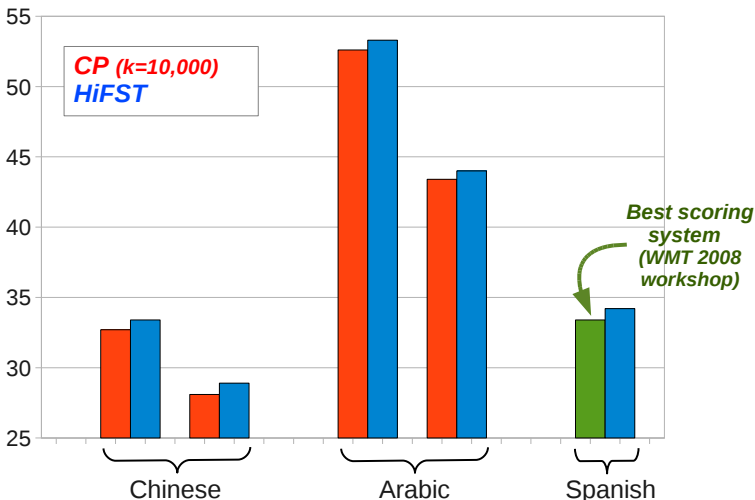
Maximum Likelihood estimates for $P(s|t)$

5-gram Language Model $P(t)$

▶ Contrast: Cube Pruning (CP) vs HiFST

Translation Results into English. Contrast CP vs HiFST

BLEU score

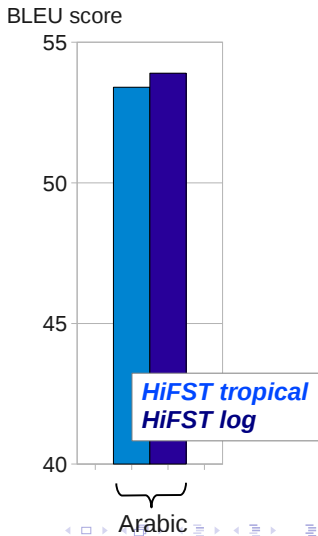


Translation Results into English. Change in Semiring

- ✓ Changing the Semiring is easy
Can have significant impact

- ▶ **Tropical Semiring**: Viterbi likelihood
- ▶ **Log Semiring**: Marginal probability
i.e. sums over all derivations

- ✓ Additional gains with no extra programming effort



Conclusions

- ✓ **HiFST generates a bigger, richer space of translation candidates**

Fewer Search Errors: 19% in Arabic, 48% in Chinese

Leveraged by subsequent rescoring techniques

- ✓ **Faster decoding times**, particularly in Arabic and Spanish

- ✓ **Simple implementation**, Google OpenFST toolkit ⁴

General, well-studied algorithms

Capable of complex semiring operations

- ✓ **HiFST system is very competitive!**

Top-3/4 in Arabic→ and Chinese→English NIST 2012 MT Evaluation (20 participants)

Top-1 in Arabic→English NIST 2009 MT Evaluation (22 participants)

Top-5 in Chinese→English NIST 2008 MT Evaluation task (20 participants)

Top-1 in Spanish→English ACL 2008 Workshop on SMT task (14 participants)

⁴C. Allauzen, M. Riley, J. Schalkwyk, W. Skut , and M. Mohri (2007), OpenFst: A General and Efficient Weighted Finite-State Transducer Library. CIAA.